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Understanding Information-Limiting Environments in Personalized News Platforms—A Systems Perspective

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Short Paper

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Abstract

Personalized news platforms (PNPs) have become increasingly popular due to their ability to provide users with tailored, relevant news content. However, their algorithmic selection of news items bears the risk of limiting the diversity of news that users are exposed to, potentially creating information-limiting environments (ILEs). As the emergence of such ILEs involves interdependent sociotechnical interactions, classical positivist approaches have failed to establish an empirically verified theory on this phenomenon. Therefore, we adopt a systems perspective to conceptualize and quantify a model describing the sociotechnical interactions in PNPs that can create ILEs. We then propose an experimental approach to simulate these interactions with real users and validate its viability through an empirical prestudy. In doing so, we contribute to IS research by providing the conceptual and methodological basis for inductive theorizing on the causes of ILEs, which is an essential prerequisite for designing effective interventions to mitigate ILE-induced risks.

Keywords: Information-limiting environments, personalized news platforms, systems perspective, echo chambers, filter bubbles

Introduction

The rise of Web 2.0 (O'Reilly, 2005) has transformed how information is produced, shared, and consumed. Unlike traditional media, online news providers commonly rely on algorithmic personalization to deliver content that is presumably the most relevant to their users. These platforms, known as personalized news platforms (PNPs), have achieved remarkable success and popularity. However, concerns have arisen that the algorithms powering PNPs, known as news recommender systems (NRSs), may inadvertently limit the breadth and diversity of presented content, promoting the formation of filter bubbles and echo chambers (Pariser, 2011; Sunstein, 2002). This phenomenon becomes particularly concerning when it leads users to reinforce their existing opinions and, thus, contributes to polarization (Helberger et al., 2018)—a state that is referred to by IS literature as an information-limiting environment (ILE) (Kitchens et al., 2020).

Although preconditions for ILEs, such as selective exposure to and biased consumption of news in PNPs, have been repeatedly studied (Bakshy et al., 2015; Kitchens et al., 2020; Shore et al., 2018), literature remains largely inconclusive regarding the specific circumstances in which these conditions occur and when they actually lead to ILEs. For example, while some studies have found evidence of filter bubbles and echo chambers in specific contexts, such as the Brexit campaign (Bastos et al., 2018) or the 2016 U.S. election (Beam et al., 2018), others have found no such evidence (Kitchens et al., 2020; Lee et al., 2014). Moreover, current research fails to present causal mechanisms that would explain when and how sociotechnical interactions within PNPs can lead to the emergence of ILEs (Schmalenbach et al., 2023; Terren & Borge-Bravo, 2021). To address these limitations, we adopt a systems perspective to capture the interdependent sociotechnical interactions between users and NRSs in PNPs. As noted by Burton-Jones et al. (2015, p. 668), "the systems perspective focuses on interactions among parts of a system and between a system and its environment" where "reciprocal relationships are typical." We argue that the systems perspective is valuable for examining ILEs in PNPs because they occur as a result of repeated interactions between users and data-driven NRSs that not only influence what users view but also adjust their recommendations based on prior users' interactions with the PNP. Moreover, we argue that experimental research is needed to isolate the causal effect of certain psychological, social, and technical antecedents of the emergence of ILEs while keeping other contextual confounding factors, such as news content or platform characteristics, constant. In line with a recent call (Fink, 2022), we therefore select an online experiment as our intended research method.

The overall objective of our research is to identify factors that promote the occurrence of ILEs in PNPs based on experimental research and to derive design and policy recommendations based on these findings. In this short paper, we take the first step towards this goal by addressing the following research question: *How can we conceptualize, formalize, and measure the sociotechnical interactions in PNPs that leads to the emergence of ILEs in a context-independent manner?* To answer this research question, we present a conceptual model of PNPs from a systems perspective, followed by its formalization in a quantitative model that captures the interactions between humans and NRSs in PNPs and provides metrics for quantifying ILEs. In doing so, we contribute to IS research in two ways. First, we extend the theoretical understanding of PNPs by conceptualizing, quantifying, and empirically testing a context-independent model of PNPs, based on a systems perspective. Second, we describe and demonstrate a novel methodological approach suitable for empirically investigating the effects of interventions aimed at decreasing the risk of ILEs in PNPs.

A Systems Perspective on PNPs

PNPs have gained popularity for delivering news items to users in a customized manner. These platforms commonly depend on data-driven NRSs that recommend news items using personalization algorithms that rely on various individual-level user data (Mitova et al., 2023). From a dynamic perspective, the interplay between the NRS's recommendations and their assessment by the PNP's users creates a reciprocal relationship, which renders it challenging to study the sociotechnical interaction in PNPs using classic positivist approaches. To address this challenge, we take on a systems perspective (Burton-Jones et al., 2015) by decomposing PNPs and their environment into interdependent components. The resulting conceptual model is shown in Figure 1. In the following, we describe the components of the conceptual model and the components' relations based on existing theory and literature.

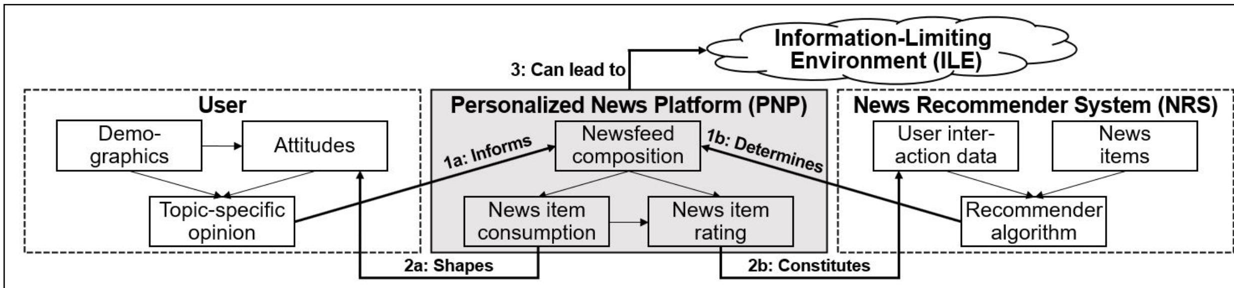

Figure 1. A Conceptual Model of PNPs From a Systems Perspective

The PNP and Its Environment

Firstly, the *users* form the *human component* of the PNP environment. Social homophily theory posits that individuals tend to form social ties with others who share similar demographics, such as age and educational attainment (McPherson et al., 2001). In addition, social contagion theory suggests that shared social ties can increase social homogeneity among individuals, such that individuals sharing social ties tend to gradually align regarding their behaviors and attitudes (Burt, 1987). In conjunction, these theories suggest that individuals having similar demographics tend to share similar attitudes, such as sociopolitical attitudes. As an example, the U.S. rural-urban political divide can be named, which refers to the phenomenon where individuals from rural areas have a tendency to lean Republican, while those residing in urban areas tend to favor Democrats (Mettler & Brown, 2022). Hence, in our conceptual model, we propose that user demographics influence user attitudes. We further propose that both user demographics and user attitudes influence the users' opinions toward specific news topics provided by the PNP. For instance, social identity theory posits that individuals sharing social ties with others having specific demographics and attitudes may experience normative pressure from their peers to conform and adopt similar perspectives on certain topics (Tajfel & Turner, 2004). Case in point, studies about gun violence in the U.S. have highlighted that opinions toward the relevance of this issue are based on demographics such as ethnicity and attitudes such as political affiliation (Schaeffer, 2021). In this vein, recent research indicates that PNP users of certain demographics (e.g., certain ages or specific educational attainments) are more vulnerable to being embedded in ILEs (Schmalenbach et al., 2023).

Secondly, the *NRS* represents the *technical component* of the PNP environment. The recommender algorithms of NRSs commonly select news items for their users based on one of two established techniques (Liao, 2023; Mitova et al., 2023). First, the content-based filtering technique can be named (Liao, 2023). This filtering technique recommends news items that are similar to prior news items consumed by the user. Second, the collaboration-based filtering technique can be named (Liao, 2023). This filtering technique selects news items that were previously consumed by other users sharing similar characteristics, such as explicitly expressed preferences. As illustrated in Figure 1, our conceptual model is able to consider both recommendation techniques. However, in this study, we focus on the collaboration-based filtering technique for two reasons. Firstly, doing so allows us to conduct experiments without needing to code the content of news items explicitly. Secondly, the news item content is not influenced by the reciprocal interactions between users and NRSs and can thus be considered a constant factor in this process (Liao, 2023).

Lastly, the *PNP* forms the *sociotechnical component* that describes how the aforementioned users consume and rate news items provided by the NRS mentioned above. First, we propose that a user's newsfeed composition—meaning which news items are recommended in the newsfeed and in what order they are positioned—influences the user's news item consumption. More precisely, the personalized positioning of news items can be reinterpreted as a type of digital nudge that reshapes the visual arrangement or salience of such items (Caraban et al., 2019). In this context, studies have shown that users tend to engage primarily with content that is highlighted or positioned more saliently (Caraban et al., 2019; Ulloa & Kacperski, 2023). Thus, we propose that users tend to primarily consume more saliently positioned news items at the expense of less saliently positioned news items. Furthermore, it is argued that PNPs tend to position opinion-confirming news items more saliently in newsfeeds (e.g., by ranking them higher) (Kitchens et al., 2020). Therefore, we further propose that the newsfeed composition influences the rating of the consumed news items provided in the newsfeed since these news items tend to align with the opinions of the users. Put differently, we propose that the users tend to rate the consumed news items recommended in the newsfeed more highly since these items are more likely to be opinion-confirming. This proposition is corroborated by past studies, which found that users are often subjected to confirmation bias, meaning that they tend to rate more highly (Taber & Lodge, 2006) and engage more (Modgil et al., 2021) with news items that reinforce their pre-existing opinions. For instance, studies experimentally revealed that supporters of more strict gun control laws rated news items expressing aligning opinions more highly than news items that opposed stricter gun control laws. Moreover, when evaluating the news items, the experiment participants uncritically accepted news items that aligned with their opinions, yet argued against news items that conflicted with their opinions (Taber & Lodge, 2006).

The Interaction Between the PNP and Its Environment

We now shift from an intra-component to an overarching inter-component perspective to discuss the interplay between the three components, as illustrated in Figure 1. Moreover, we discuss how this interplay can promote ILEs emergence and describe the consequences for users embedded in such ILEs. In our conceptual model, we propose that the PNP composes a personalized newsfeed for each individual user. In particular, the user's opinion about a specific topic *informs* the newsfeed composition process as it allows the PNP to identify potentially relevant news items (relation 1a). The NRS considers this information when it *determines* the exact composition of the user's personalized newsfeed by ranking the news items using its recommender algorithm (relation 1b). The user then accesses their newsfeed to consume the recommended news items, which further *shapes* the user's attitudes (relation 2a). Simultaneously, the NRS associated with the PNP stores the user's explicit (e.g., likes) or implicit rating (e.g., click-through rates) of the news items in its database. Combined, this rating *constitutes* user interaction data that will then be used for future recommendations (relation 2b). This repeating interplay can foster a self-reinforcing cycle that limits users' exposure to diverse viewpoints, thus restricting their access to a broader range of information. In other words, this interplay *can lead to* users becoming gradually embedded in ILEs (relation 3).

The concept of ILEs refers to how "social network homophily and algorithmic filtering restrict individuals from accessing diverse information sources, shielding them from information that challenges their beliefs and leading to the adoption of more extreme viewpoints" (Kitchens et al., 2020, p. 1620). Social homophily, the tendency for similarity to foster connections (McPherson et al., 2001), describes that PNP users tend to connect and interact with news items that match their values and characteristics. Algorithmic filtering in the context of PNPs refers to the algorithms in the associated NRSs that recommend personalized news items to PNP users. While social homophily and algorithmic filtering alone can lead to ILEs, it is usually their combination that exacerbates their emergence. The example of news consumption on Reddit demonstrates this (Kitchens et al., 2020). When users follow subreddits that align with their political attitudes, they receive more news items from those subreddits, and the platform recommends thematically similar subreddits. Users may follow recommended subreddits as they reflect their interests and opinions, perpetuating the cycle that leads to selective exposure and consumption, which can have both positive and negative outcomes. On the one hand, users receive news items that they deem relevant, which can prevent cognitive dissonance and related psychological stress (Festinger, 1962). On the other hand, the lack of conflicting views and values caused by limited exposure and consumption diversity (Mattis et al., 2022) can lead to ILEs, where personal biases and radicalization are fostered (Grover & Mark, 2019). ILEs can further inhibit opinion shifts driven by critical reflection due to the lack of triggers that generate the desire to achieve cognitive consistency (Festinger, 1962). On a societal level, ILEs can contribute to social fragmentation and radicalization, which can result in conflicts between societal groups (Kitchens et al., 2020).

Quantifying Sociotechnical Interaction and ILEs in PNPs

In this section, we introduce a quantitative model that captures the components and relations of the conceptual model, as illustrated in Figure 1. The quantitative model is designed to empirically simulate the sociotechnical interaction patterns that lead to ILEs in PNPs while conducting online experiments. Although the model requires an initial assessment of the users' characteristics, such as demographics, sociopolitical attitudes, and opinions on specific news topics via a pre-experimental survey, no preliminary knowledge or manual coding of news items is necessary. The model outlines the sociotechnical interactions within PNPs in two stages. Firstly, it describes how an NRS's *collaborative filtering algorithm* CF recommends *news items* N to *users* U, resulting in a sorted *newsfeed* F (relations 1a, 1b). Secondly, it explains how a user's consumption and *rating* R trigger a re-evaluation of both the user's opinion and the characteristics of the average user who positively rates the news item (relations 2a, 2b). Based on evidence obtained from this interaction, the model enables us to capture tendencies for the occurrence of ILEs (relation 3). In particular, this is achieved by measuring the diversity of news items in the newsfeed *(i.e., exposure diversity)* and in the subset of news positively rated by a user *(i.e., consumption diversity)*. In the following, we will describe how the model captures the two interaction stages, followed by an explanation of how ILEs can be quantified.

Newsfeed Composition

This section describes how the PNP composes a user's newsfeed based on the user's opinion and the NRS's data (i.e., relations 1a, 1b). Given is a finite set of n news items $\mathcal{N} = \{N_1, N_2, \ldots, N_n\}$ and a finite set of u users $\mathcal{U} = \{U_1, U_2, \ldots, U_u\}$. To model the collaborative filtering technique, which recommends news items based on the consumption preferences of users with similar characteristics, we define the set of user characteristics C of user U_i as $C(U_i) = \left(C_i^1, C_i^2, \ldots, C_i^c\right)$ for any number c of user characteristics that the NRS considers. To capture the aggregated characteristics of users who show a consumption preference for a particular news item, we position every news item into a c-dimensional space, where each dimension represents one user characteristic. For any news item N_j, we denote its position in this space as a vector $P_N(N_j) = \left(P_j^1, P_j^2, \ldots, P_j^c\right)$. Likewise, we can position any user U_i into this space based on their characteristics by simply defining $P_U(U_i) = C(U_i)$. Utilizing the positions of news items and users, we can establish metrics to compute the distance d between a given user U_i and news item N_j, indicating the difference between the characteristics of user U_i and the ones of the average user who positively rates N_j. Albeit any distance measure could qualify for this purpose, we use the c-dimensional Euclidean distance:

$$d(U_i, N_j) = \sqrt{\sum_{k=1}^{c} \left(P_j^k - C_i^k\right)^2} \tag{1}$$

Employing this metric, we define the collaborative filtering-based recommender algorithm as a function CF that determines the position of any news item N_j in the newsfeed of user U_i:

$$CF(U_i, N_j) = \min\left(x \in [1, n] \mid \forall y < x : d(U_i, N_y) \leq d(U_i, N_x)\right) \tag{2}$$

Whenever there are multiple news items with equivalent distance to the user, we specify that CF will rank them in random order. We then define the newsfeed $F(U_i)$ of user U_i as the sorted sequence of the first $f \leq n$ news items with incremental distance to the user, that is: $F(U_i) = \langle N_j \mid CF(U_i, N_j) \in [1, f]\rangle$. We subsequently denote the items in the newsfeed of user U_i as $F(U_i) =: \left\langle F_i^1, F_i^2, \ldots, F_i^f \right\rangle$.

User and News Item Repositioning

We now describe how the PNP evaluates the user's rating of the news items in their newsfeed to re-compute the positions of the user and the news items (i.e., relations 2a, 2b). In our model, a user U_i rates a news item N_j in their newsfeed based on a set of r criteria, e.g., *likeability*, *quality*, or *relevance*. The user's rating of the news item is denoted as $R(U_i, N_j) = \left(R_{i,j}^1, R_{i,j}^2, \ldots, R_{i,j}^r\right) \in [0, 1]^r$, and their overall rating is defined as the arithmetic mean $\overline{R}(U_i, N_j) = r^{-1} \cdot \sum_{k=1}^{r} R_{i,j}^k$. After a rating event, the NRS shifts the position of the news item N_j in the c-dimensional space to account for the rating when recommending the item to subsequent users (relation 2b). Additionally, we assume that the user's position is shifted to account for differences between the user's initial assessment by the system and their actual consumption behavior (relation 2a). As the system has no initial information about where to position news items (i.e., *cold start problem* (Lika et al., 2014)), each news item is initialized with a weight of $w(N_j) := 0$. In contrast, based on an explicit assessment of user characteristics prior to their interaction with the NRS, the system already knows some characteristics of the users and therefore assigns them a weight of $w(U_i) := w_{init} > 0$. The weight of a rated news item is increased by 1 after each rating event, while the weights of users remain constant. We use a *user shift factor* $\rho_U(U_i, N_j) = w(N_j) \cdot (w(U_i) + w(N_j))^{-1}$ and a corresponding *news item shift factor* $\rho_N(U_i, N_j) = w(U_i) \cdot (w(U_i) + w(N_j))^{-1}$ to account for the system's relative knowledge of news items and users. For instance, if $w(U_i) = 15$ and $w(N_j) = 5$, the news item is shifted three times further than the user. Based on this calculation, the shift vectors S_U and S_N for the users and news items are given as follows:

$$S_U(U_i, N_j) = \rho_U(U_i, N_j) \cdot \overline{R}(U_i, N_j) \cdot (P_U(U_i) - P_N(N_j)) \tag{3a}$$
$$S_N(U_i, N_j) = \rho_N(U_i, N_j) \cdot \overline{R}(U_i, N_j) \cdot (P_N(N_j) - P_U(U_i)) \tag{3b}$$

Note that the shift vectors are collinear to the difference vector between the user's and the news item's position. While the length and direction of the overall shift are influenced by the user's rating, its distribution between the user and the news item is determined by the shift factors ρ. To regulate the magnitude of the overall shift, we also introduce a constant parameter $\gamma \in [0, 1]$. We can then obtain the new position P' of user U_i and news item N_j by adding the product of γ and the shift vector to their current position, as follows:

$$P'_U(U_i) = P_U(U_i) + \gamma \cdot S_U(U_i, N_j) \quad \text{and} \quad P'_N(N_j) = P_N(N_j) + \gamma \cdot S_N(U_i, N_j) \tag{4}$$

Quantifying ILEs

By assessing the relative diversity of news items a user U_i is exposed to or consumes, our model can assess the occurrence of ILEs (i.e., relation 3). To do so, we introduce a diversity measure D that measures the average pairwise distance in a set of news items. While the *exposure diversity* $D_E(F(U_i))$ describes the diversity of news items in an individual user's newsfeed $F(U_i)$, the *supply diversity* $D_S(\mathcal{N})$ captures the diversity in the overall set of news items $\mathcal{N}$. We compute the exposure diversity $D_E(F(U_i))$ for a user U_i as follows:

$$D_E(F(U_i)) = \left(\frac{f(f-1)}{2}\right)^{-1} \cdot \sum_{x,y>x}^{f} d(F_i^x, F_i^y) \tag{5}$$

Additionally, we can measure the *consumption diversity* $D_C(F(U_i))$, which describes the diversity among news items that receive a positive rating from user U_i. To do so, we multiply the respective exposure diversity value with the average rating of the two news items involved:

$$D_C(F(U_i)) = \left(\frac{f(f-1)}{2}\right)^{-1} \cdot \sum_{x,y>x}^{f} d(F_i^x, F_i^y) \cdot \frac{\overline{R}(U_i, N_x) + \overline{R}(U_i, N_y)}{2} \tag{6}$$

When comparing these metrics, we can assess the extent to which ILEs occur in the PNP. For instance, if $D_E(F(U_i)) < D_S(\mathcal{N})$, the news items in user U_i's feed show a selection bias towards users with similar characteristics. Furthermore, if $D_C(F(U_i)) < D_E(F(U_i))$, it suggests that the user's news consumption behavior contributes to an ILE, potentially biasing the recommendations received by future users. The model also allows for more advanced computations, such as the ratio between the size of *information clusters* (i.e., small areas with a high density of news items) and the distance between them, which could serve as a measure of group polarization. However, such calculations go beyond the scope of the current study.

Method and Preliminary Evaluation

To confirm that our quantitative model correctly captures the interaction that leads to the emergence of ILEs, as depicted in Figure 1, we conducted a single-group prestudy with $u = 31$ participants without manipulating independent variables. A prototype of a PNP was implemented, adhering to our model, and $n = 87$ news items about universal basic income were adapted from an ideologically diverse set of nine online news outlets, blinded, and standardized[1]. Figure 2 shows the observed exposure and consumption diversity relative to the system's supply diversity (normalized to 100%) during the users' successive interaction events.

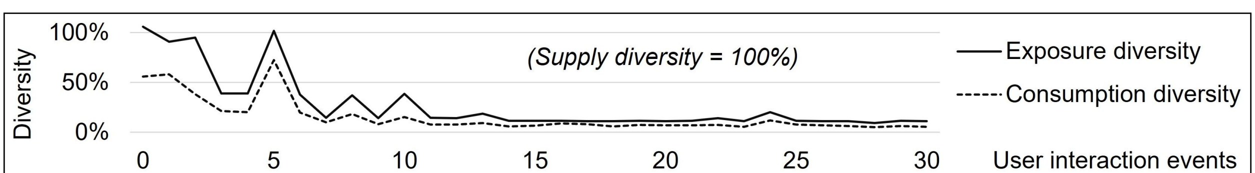

Figure 2. Exposure and Consumption Diversity During User Interaction Events

[1]Source code, news items, and implementation parameters can be found at https://github.com/kianschmalenbach/news-2023/.

We selected the news topic since it is well-known and sufficiently controversial for diverse and balanced opinions, yet not too polarized, such that potential opinion shifts in users can be observed. Users were presented with a newsfeed of length $f = 12$ and rated their agreement with each news item, as well as its quality, relevance, and ability to reach a consensus. We then calculated the exposure and consumption diversity for each user utilizing equations (5) and (6), respectively. Our findings illustrate how the NRS, after an initial stabilization phase, expectedly, induces a reduced exposure diversity that falls notably below the supply diversity and appears to converge to about 10% relative diversity. This exemplifies the impact PNPs can have on users' news exposure diversity, manifesting a technical bias. Additionally, the consumption diversity is, on average, about 40% lower than the exposure diversity and converges at about 6% of the supply diversity, thereby demonstrating the limiting effect of cognitive biases on news consumption. In turn, this selective consumption leads to reduced exposure diversity for the subsequent recommendations. This interplay continues until an equilibrium is reached, where exposure and consumption continually align, illustrating Burton-Jones et al.'s (2015) explanation of how negative feedback can cause equilibria. While our results are exemplary and do not contribute directly to our theory-building process, they serve as a proof of concept, indicating that our approach is feasible and can be extended to study ILE antecedents in PNPs.

Discussion and Outlook

In the face of ongoing concerns over fake news, misinformation, and polarization in online news platforms and social media, it is crucial to identify the circumstances that foster ILEs (Kitchens et al., 2020). However, to be able to effectively counteract ILE emergence and mitigate the associated adverse consequences, research has yet to establish an empirically validated theory that adequately explains the factors causing ILEs to arise (Schmalenbach et al., 2023; Terren & Borge-Bravo, 2021). In this short paper, we contribute towards closing this gap by adopting a systems perspective to develop a conceptual model that describes the interdependent ILE-inducing relations between PNPs and their environment (Burton-Jones et al., 2015). We then extend our contribution by deducing a quantified version of our model, before empirically evaluating its effectiveness for investigating ILE emergence through online experiments (Fink, 2022).

Intended Method and Expected Contribution

This research holds two overarching objectives that extend beyond our current contributions. Firstly, we aim to inductively develop an explanatory theory of ILE emergence from a systems perspective by identifying specific independent and moderating variables that causally impact ILE formation, such as demographic attributes, personal attitudes, technical characteristics of NRSs, and psychological factors in news item evaluation. Subsequently, we intend to test the effect of these variables on ILE emergence through online experiments, while controlling for context-specific factors such as topics, news items, and platform design characteristics. Secondly, we aim to design and evaluate respective interventions to counteract ILEs, encompassing pedagogical approaches such as salience nudges and literacy training as well as technical manipulations including user control mechanisms (Schmalenbach et al., 2022). Evaluating these interventions through experiments will offer robust internal validity concerning their effectiveness, allowing us to formulate practical recommendations for platform operators and policymakers aimed at mitigating ILEs.

Our approach shows overlap with prior attempts to model factors of ILE emergence. For example, Geschke et al. (2019) introduced the triple-filter-bubble model as a meta-theoretical framework describing three types of filtering processes, namely individual, social, and technological filters. However, this framework relies purely on agent-based modeling and is thus conceptual in nature. Therefore, we extend their work by providing a quantified model that can be applied for empirical tests with real users. More generally, our experimental approach presented above aims to bridge a significant theoretical gap in existing literature between simulation-based studies (de Arruda et al., 2022; Geschke et al., 2019; Magdaci et al., 2022), descriptive field studies conducted using context-specific data from PNPs such as Twitter, Facebook, or Reddit (Beam et al., 2018; Kitchens et al., 2020; Shore et al., 2018), and studies based on users' self-reported survey data (Boulianne et al., 2020; Strauß et al., 2020). While these studies provide important insights on conceptual and empirical aspects of ILE emergence in PNPs, they share the limitation that their results depend on simulations, context-specific or self-reported data and, therefore, cannot draw practically applicable conclusions on the context-independent behavioral effect of specific interventions.

Limitations and Future Research Opportunities

Our study has three limitations. Firstly, our collaboration-based filtering technique requires a focus on a single news topic and neglects other recommendation approaches. Therefore, future research should account for content-based news recommendations and multiple news topics. Secondly, our proposed experimental design relies on singular user interaction events, neglecting the influence of long-term interaction with PNPs on ILE formation captured in our model. Thus, further research should investigate longitudinal effects on ILE emergence through repeated user interaction. Lastly, our study's external validity might be limited if real-world PNP conditions differ significantly from our model's assumptions. Consequently, subsequent research should evaluate our design recommendations' impact in the field by applying them to real PNPs.

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